Spatial Statistics for Analyzing Data in Cinematic Virtual Reality

Sylvia Rothe
LMU Munich
Munich, Germany
sylvia.rothe@ifi.lmu.de

Heinrich Hußmann
LMU Munich
Munich, Germany
heinrich.hussmann@ifi.lmu.de

ABSTRACT

Cinematic Virtual Reality has been increasing in popularity over the last years. Watching 360° movies with head mounted displays, viewers can freely choose the direction of view, and thus the visible section of the movie. In order to explore the viewers' behavior, methods are needed for collecting and analyzing data. In our experiments we compare the viewing behavior for movies with spatial and non-spatial sound and tracked the head movements of the participants. This work-in-progress describes two approaches of spatial statistics – analysis of Space Time Cubes and Getis Ord Gi* statistic – for analyzing head tracking data.

CCS CONCEPTS

• **Multimedia Information Systems** → Artificial, augmented, and virtual realities; • **Vision and Scene Understanding** → Video analysis

KEYWORDS

Cinematic Virtual Reality; 360° movie; spatial statistics; spatial sound; space time cube; Getis Ord Gi*

1 INTRODUCTION

In **Cinematic Virtual Reality (CVR)** the viewer is inside the scene, and can freely choose the direction of view. Accordingly, the viewer determines the visible section of the movie, while in traditional movies the filmmaker chooses the shown part. In our work we examine where the participants are looking without any search tasks. We investigate if they follow several cinematic cues such as sounds and movements and compare the viewing behaviour for movies with spatial sound and non-spatial sound.

AVI '18, May 29-June 1, 2018, Castiglione della Pescaia, Italy

ACM ISBN 978-1-4503-5616-9/18/05.
https://doi.org/10.1145/3206505.3206561

To explore this, we logged the head movements of the participants and visualized them in several ways. In a first step, we generated heatmaps for finding clusters in the data. However, heatmaps are not sufficient for inferential statistics to make statements about confidence. Therefore, **statistical methods** are needed for determining the significance of the clusters – for identifying hotspots. The term **hotspot** is used in the literature in different ways. In our work, a hotspot is a cluster with high values identified by statistical methods using confidence levels. In our dataset, the value is the number of views in a space-time segment.

Nielsen et al. [17] compared a moving firefly with forced rotation and no guidance. Using a questionnaire, they figured out that the firefly was more helpful than forced rotation. Furthermore, the results demonstrate that forced rotation may decrease the presence. For determining which cues attract the attention of the viewer and which can change the viewing direction, we decided not to use questionnaires. Instead, the head direction was recorded and evaluated to obtain more precise results.

Several researches investigated head movements for still images [21,25,4]. In our studies the images are varying continuously, which needs a new approach for analyzing. Additionally, we determine significant hotspots by spatial statistic methods.

The collected data are **spatiotemporal data** – data which have a space and a time component. This type of data is often used in geographical researches, so we applied some methods of spatial statistics which are used in geography: Space Time Cube analysis and hotspot analysis using Getis-Ord Gi* statistic.

Space Time Cubes (STC) were introduced by Hägerstrand in 1970 [10]. The use of STC for analyzing geographical data has been studied in [12,13,9]. The method is also applicable for investigating movements [2,5,6] or eye tracking data [1,15]. In our work we adapt this method for analyzing head tracking data of users watching CVR videos. For the inferential statistics part we used the Getis-Ord Gi* statistic. This method was established by Getis and Ord [8,18] for analyzing spatial data. Songchitruksa et al. [24] used the Getis-Ord spatial statistic for identifying hotspots.

2 SPATIAL ANALYSIS AND STATISTICS

2.1 Space Time Cubes

A method of investigating spatiotemporal data with two space coordinates is to analyze Space Time Cubes (STC). In these cubes two coordinates represent the space and the third one the time. With this technique the data can be visualized and explored in a comfortable way. Using GIS software (Geographic Information System) we inspected space time cubes showing the counts of incidents – in our case "how often" users looked at a certain area segment within a specific time frame, as shown in fig. 1. Two STCs were generated, one for the data with spatial sound and the other one for non-spatial sound.

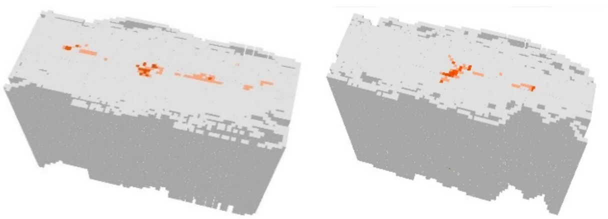

Figure 1: The space time cubes for both groups (left: movie with spatial sound, right: movie with non-spatial sound)

In this way we could see for every time interval (we used 1s) where the most views are. However, the correlation between the points (in space and time) were not taken in account in this step. For this it needs the hotspot analysis.

2.2 Getis-Ord Gi* Statistic

For finding statistical significant hotspots, methods of spatial statistics can be applied. These methods take into account the neighbor relations between the space-time segments in the STC.
The collected data are point incident data. Point incident data are points connected to an event – in our case the viewer looked to this point. We were interested in significant clusters. To find such clusters, we used the Getis-Ord Gi* statistic [8]. This statistical method requires values for the investigated points. In order to use this method, the incident data were aggregated and incident counts established. The incident counts - in our case the number of views in a segment - are the attribute values which are analyzed by the method. Using the spatial statistic tools of the ArcGIS Pro Software again, we generated STCs displaying hotspots (fig. 2).

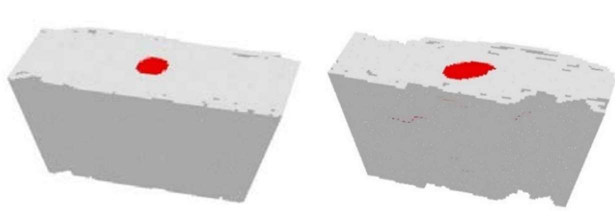

Figure 2: The space time cubes with significant hotspots for both groups, (left: movie with spatial sound, right: movie with non-spatial sound)

For every point in the STC the p value can be displayed by double-clicking on the point. The p value represents the probability that the observed pattern was created randomly. A small p value means that the pattern is most likely caused by a cluster. Segments with p values smaller than 0.01, which means 99% confidence, are displayed in red.

With this method we compared the two data sets. We changed the time slices step by step by a slider (fig. 3) and compared the hotspots generated by using spatial sound with the hotspots generated using non-spatial sound.

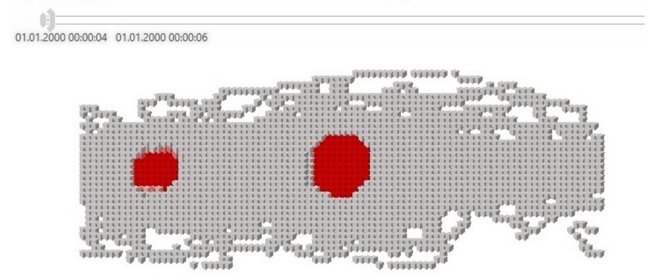

Figure 3: A slider is used to navigate in the STC by changing the time slice.

3 USER STUDY

For our study we utilized a 9:26 min 360° movie ("Crossing Border") made by young filmmakers. This movie was produced with spatial and non-spatial sound and contains many cues for guiding the viewer, for example speaking persons, movements and sounds. The participants sat on a swivel chair while watching the movie using a head mounted display (Samsung Gear VR with Samsung Galaxy S6) and headphones. After watching the movie, a short unstructured interview followed.

Our study relied on a between-subject test design. The movie was shown to two groups. The first group (20 participants aged between 23 and 65, mean=31.5, 10 women and 10 men) watched the movie with spatial sound, the other group (20 participants aged between 21 and 67, mean=34.7, 8 women and 12 men) with non-spatial sound. Each group included 6 participants watching CVR for the first time, and 3 experienced participants. The other participants used CVR occasionally. There was no special task for the participants.

3 FUTURE WORK AND CONCLUSION

Our next step is to describe and discuss the results of the user study. The outcomes can be used for integrating cues in a movie for guiding the attention of the viewer to things which are important for the story.

Further investigations are necessary to explore the viewers' behaviour in Cinematic Virtual Reality. Methods of spatial statistics are suitable to assist in these researches.

REFERENCES

1 Blascheck, T., Kurzhals, K., Raschke, M., Burch, M., Weiskopf, D., and Ertl, T. Visualization of Eye Tracking Data: A Taxonomy and Survey. In [illegible] (2017).

2 Cho, Nahye and Kang, Youngok. Space-time density of field trip trajectory: exploring spatio-temporal patterns in movement data. [illegible], 25 (2017), 141-150.

4 De Abreu, Ana, Ozcinar, Cagri, and Smolic, Aljosa. Look around you: Saliency maps for omnidirectional images in vr applications. In [illegible] 2017 [illegible] (2017), 1-6.

5 Demšar, Urška and Virrantaus, Kirsi. Space--time density of trajectories: exploring spatio-temporal patterns in movement data. [illegible], 24 (2010), 1527-1542.

6 Ding, Linfang, Krisp, Jukka M., Meng, L., Xiao, G., and Keler, A. Visual exploration of multivariate movement events in space--time cube. AGILE 2016 (2016).

8 Getis, Arthur and Ord, J. Keith. The analysis of spatial association by use of distance statistics. [illegible], 24 (1992), 189-206.

9 Guo, Diansheng, Chen, Jin, MacEachren, Alan M., and Liao, Ke. A visualization system for space-time and multivariate patterns (vis-stamp). IEEE [illegible], 12 (2006), 1461-1474.

10 Hägerstraand, Torsten. What about people in regional science? [illegible], 24 (1970), 7-24.

12 Kraak, Menno-Jan. The space-time cube revisited from a geovisualization perspective. In [illegible] 21 [illegible] (2003), 1988-1996.

13 Kristensson, Per Ola, Dahlback, Nils, Anundi, Daniel et al. An evaluation of space time cube representation of spatiotemporal patterns. IEEE [illegible], 15 (2009), 696-702.

15 Li, Xia, Çöltekin, Arzu, and Kraak, Menno-Jan. Visual exploration of eye movement data using the space-time-cube. In [illegible] (2010), 295-309.

17 Nielsen, Lasse T., Møller, Matias B., Hartmeyer, Sune D., Ljung, Troels, Nilsson, Niels C., Nordahl, Rolf, and Serafin, Stefania. Missing the point: an exploration of how to guide users´attention during cinematic virtual reality. In [illegible] 22 [illegible] ACM [illegible] (2016), 229-232.

18 Ord, J. Keith and Getis, Arthur. Local spatial autocorrelation statistics: distributional issues and an application. [illegible], 27 (1995), 286-306.

21 Rai, Yashas, Gutiérrez, Jesús, and Le Callet, Patrick. A dataset of head and eye movements for 360 degree images. In [illegible] 8 [illegible] ACM [illegible] (2017), 205-210.

24 Songchitruksa, Praprut and Zeng, Xiaosi. Getis-Ord spatial statistics to identify hot spots by using incident management data. [illegible] (2010), 42-51.

25 Upenik, Evgeniy and Ebrahimi, Touradj. A simple method to obtain visual attention data in head mounted virtual reality. In IEEE [illegible] 2017 (2017).